Financial contagion and the TIR-MIDAS model

Ye, W., Jiang, K., Liu, X.

University of Nottingham Ningbo China, 199 Taikang East Road, Ningbo, 315100, China

First published 2020

This work is made available under the terms of the Creative Commons Attribution 4.0 International License:
http://creativecommons.org/licenses/by/4.0

The work is licenced to the University of Nottingham Ningbo China under the Global University Publication Licence:

https://www.nottingham.edu.cn/en/library/documents/research-support/global-university-publications-licence.pdf

University of Nottingham
UK | CHINA | MALAYSIA

Financial contagion and the TIR-MIDAS model

Wuyi Ye* Kunliang Jiang† Xiaoquan Liu‡

April, 2020

Abstract

In this paper, we develop a new approach for modeling financial contagion. It is combines the tail index regression, which specifically describes fat tails in asset returns, with the information contained in macroeconomic variables via the mixed data sampling technique in order to identify contagion in international equity markets. Empirically, our model successfully detects structural breaks in the tails of equity return distributions between the US and five developed economies during the recent Great Recession, and identifies the existence of contagion for two of them. The findings underscore our method as a flexible and reliable alternative for examining contagion.

JEL code: C58, G15

Keywords: Hill Estimator; Time Series Analysis; Financial Crisis; Macroeconomic Variables.

*Department of Statistics and Finance, University of Science and Technology of China, Hefei, China. Email: wyye@ustc.edu.cn.

†Department of Statistics and Finance, University of Science and Technology of China, Hefei, China. Email: kunliang@mail.ustc.edu.cn.

‡Corresponding author. University of Nottingham Business School China, University of Nottingham Ningbo, China. Email: xiaoquan.liu@nottingham.edu.cn. Phone: +86 574 88180000 Ext 8207.

1 Introduction

To what extent do global equity markets co-move and what are the driving factors behind contagion are topical issues in the international finance and econometrics literature. Different methodologies have been formulated to address these issues, including the co-integration analysis (Bekaert et al., 2005), the vector autoregression (Favero and Giavazzi, 2002; Yang and Bessler, 2008), dynamic panel threshold models (Mensi et al., 2016), the flexible copula functions (Rodriguez, 2007; Ye et al., 2012), and, more recently, the quantile association regression model (Ye et al., 2017).

In this paper, we define contagion as a significant increase in the probability of an equity market crash in one economy, conditional upon a crisis occurring in another economy (Pericoli and Sbracia, 2003). We model market crash by the *tail index*, a statistical measure describing the tails of a distribution (Hill, 1975). For slowly-moving Pareto-type distributions such as those for financial time series, the tail index α is positive; the smaller the α, the more likely that a distribution produces extreme values (Beirlant et al., 2008; Gomes et al., 2008; Huisman et al., 2001). Hence, the tail index lends itself naturally to capturing contagion.

Motivated by this, we measure the probability of a crash via the tail index of market-wide index returns: financial contagion exists if the tail index of one market decreases as a result of a drop in the tail index of another market. Specifically, our new model is based on the tail index regression (TIR) of Wang and Tsai (2009) and utilizes information contained in macroeconomic variables of the originating market. The mixed data sampling (MIDAS) technique of Ghysels et al. (2004) and Ghysels et al. (2007), a popular model to extract information from financial time series data of different frequencies, is adopted (see Fang et al., 2018; Lei et al., 2019, for example). Hence, it is called the TIR-MIDAS model.

As structural breaks are likely to take place during financial crises (see Jin, 2016; Wei et al., 2019, for example), it is possible that the TIR coefficients will experience significant changes during the sample period. We allow data to determine potential structural breaks via the maximum likelihood estimation. Hence, we avoid arbitrarily dividing data into subsamples. Once structural breaks are identified, the existence of contagion is assessed by comparing TIR coefficients prior to and after the change points.

Empirically, we implement our TIR-MIDAS model to examine contagion between the US and five major developed economies, namely Australia, Germany, Japan, Hong Kong, and the UK, using daily equity index levels. We also take advantage of the information content of monthly US macroeconomic indicators, i.e., money supply, industrial production, consumer confidence index, employed population, retail sales, consumer price index, and purchasing manager index via the MIDAS technique. The sample period is from January 2000 to December 2018. Our empirical analyses reveal interesting findings. First, one significant structural break exists for all test markets, and it takes place in 2008 except for Hong Kong whereby the change point is in August 2007. Second, it is interesting to note that the inclusion of macroeconomic variables hardly affects the location of structural breaks. Finally, we show that contagion exists between the US as the originating economy and Germany and Hong Kong as the recipient markets.

Our paper contributes to the literature in two ways. First, we develop a novel TIR-MIDAS framework, which is able to incorporate information in macroeconomic variables to the study of tail behavior of asset returns in capturing contagion. Second, we offer supportive empirical evidence that the TIR-MIDAS model is able to successfully identify the existence and location of structural breaks and contagion. Our results are of clear relevance to international portfolio managers who allocate their wealth across the global equity markets.

The rest of the paper is organized as follows. Section 2 outlines the TIR-MIDAS model and the MLE estimation to determine structural breaks. In Section 3, we describe data and analyze empirical results. Finally, Section 4 concludes.

2 Methodology

The TIR-MIDAS model

According to the Fisher-Tippett theorem, there exists a slowly-varying function $L(x)$ that when $x \to \infty$, the distribution of returns can be approximated as $F(x) = 1 - L(x)x^{-\alpha}$. The second-order expansion of $F(x)$ is expressed as follows:

$$F(x) = 1 - mx^{-\alpha}(1 + qx^{-\beta}), \tag{1}$$

where m and q are scale parameters, and α and β are tail index coefficients. To measure the tail index α, Wang and Tsai (2009) extend the Hill estimator and propose a tail index regression model, which assumes that α is a function of other exogenous variables. We assume that $Y_i \in R^1$ is sampled from a heavy-tailed distribution, and $\mathbf{X}_i = (X_{i1}, \cdots, X_{ip})' \in R^p$ is observable exogenous variables. We assume that: $F(y|\mathbf{x}) = P(Y_i \leq y|\mathbf{X}_i = \mathbf{x}) = 1 - y^{-\alpha(\mathbf{x})}L(y; \mathbf{x})$.[1] When y is sufficiently large, we obtain the conditional density function $f(y|\mathbf{x})$ as follows:

$$f(y|\mathbf{x}) \approx \alpha(\mathbf{x})y^{-\alpha(\mathbf{x})-1}, \tag{2}$$

where $\alpha(\mathbf{x}) = \exp(\mathbf{x}'\theta)$, $\theta \in R^p$ is the regression coefficient vector.[2]

Follow Asgharian et al. (2013), we adopt the MIDAS specification to incorporating low-frequency macroeconomic factor in $\mathbf{x}'\theta$. We decompose the observation $\mathbf{x}_i'\theta$ of day i in $\mathbf{x}'\theta$ into two components: a short-run transitory component, $\beta_3 r_{i,\tau}$, and a long-run one, α_τ, so we have the following:

$$\mathbf{x}_i'\theta = \alpha_\tau + \beta_3 r_{i,\tau}. \tag{3}$$

We treat τ as a month, so that $r_{i,\tau}$ is the return on day i of month τ. We further assume that α_τ is affected by lagged monthly stock index returns and macroeconomic factors, z_τ. Hence, α_τ can be defined as follows:

$$\alpha_\tau = \beta_0 + \beta_1 z_\tau + \beta_2 \sum_{k=1}^{K} \phi_k(w) R_{\tau-k}, \tag{4}$$

where β_0 is the intercept, β_1, β_2, β_3 capture the impact of macroeconomic variables, lagged stock index returns, and current stock index returns, respectively. They, alongside w, need to be estimated; and K is the number of periods over which the model smooths returns $R_\tau = \sum_{i=(\tau-1)N+1}^{\tau \times N} r_{i,\tau}$. The weighting framework used in Eq.(4) is described by the beta polynomial (Engle et al., 2013): $\phi_k(w) = \frac{(1-k/K)^{w-1}}{\sum_{l=1}^{K}(1-l/K)^{w-1}}$, where $k = 1, 2, 3, ..., K$. When $w > 1$, the deceleration rate is determined by the size of w. We let $K = 36$ and $N = 22$ following Asgharian et al. (2013).[3]

With the Hill estimator, the sample used for parameter estimation could be controlled by the threshold

[1] The argument for this assumption is available upon request from the authors.
[2] The proof for Eq.(2) is available upon request from the authors.
[3] We have performed robustness tests for $N = 21$ and 23 and obtain qualitatively similar results. These results are available upon request from the authors.

ω_n. Conditional on $\mathbf{x}$ and $Y > \omega_n$, we have the following:

$$f(y|\mathbf{x}, Y > \omega_n) \approx \alpha(\mathbf{x}) \left(\frac{y}{\omega_n}\right)^{-\alpha(\mathbf{x})} y^{-1}. \tag{5}$$

In the empirical analysis, we use negative values of stock returns. We express the logarithmic likelihood function as follows:

$$K_n(\theta) = -\ln L(\theta) = \sum_{i=1}^{n} \{\exp(\mathbf{x}_i'\theta) \log(Y_i/\omega_n) - \mathbf{x}_i'\theta\} I(Y_i > \omega_n), \tag{6}$$

where $I(\cdot)$ is the indicator function, and the threshold ω_n can be determined by minimizing $K_n(\theta)$ in a certain range of ω_n. The median of this range is determined by the estimation method proposed by Wang and Tsai (2009). At this time, $\mathbf{x}_i'\theta$ does not contain long-term components.

<u>The test of structural break</u>

We are interested in assessing if structural breaks exist for the parameter vector $\theta = [\beta_0, \beta_1, \beta_2, \beta_3, w]$. Suppose one structural break exists, $\alpha(\mathbf{x})$ can be re-written as follows:

$$\alpha(\mathbf{x}) = \begin{cases} \exp(x_i'\theta^{(1)}) & \text{if } 1 \leq i \leq t_0 \\ \exp(x_i'\theta^{(2)}) & \text{if } t_0 < i \leq n \end{cases} \tag{7}$$

with $\theta^{(1)} = [\beta_{01}, \beta_{11}, \beta_{21}, \beta_{31}, w_1]$ and $\theta^{(2)} = [\beta_{02}, \beta_{12}, \beta_{22}, \beta_{32}, w_2]$. We test the null and the alternative hypotheses as follows:

$$H_0 : \theta^{(1)} = \theta^{(2)} \leftrightarrow H_1 : \theta^{(1)} \neq \theta^{(2)}.$$

If the null hypothesis is rejected, t_0 is the structural break. When $Z_n = \max_{1 \leq k \leq n}(-2 \log \Lambda_k)$ is very large, the null hypothesis is rejected. Where $-2 \log \Lambda_k$ is the likelihood ratio statistics and is expressed as follows:

$$-2 \log \Lambda_k \quad = \quad -2[\sum_{i=1}^{k} \{\exp(\mathbf{x}_i'\hat{\theta}^{(1)}) \log(Y_i/\omega_n) - \mathbf{x}_i'\hat{\theta}^{(1)}\} I(Y_i > \omega_n) \tag{8}$$

$$+ \sum_{i=k+1}^{n} \{\exp(\mathbf{x}_i'\hat{\theta}^{(2)}) \log(Y_i/\omega_n) - \mathbf{x}_i'\hat{\theta}^{(2)}\} I(Y_i > \omega_n)$$
$$- \sum_{i=1}^{n} \{\exp(\mathbf{x}_i'\hat{\theta}) \log(Y_i/\omega_n) - \mathbf{x}_i'\hat{\theta}\} I(Y_i > \omega_n)]$$

where $\hat{\theta}^{(1)}$, $\hat{\theta}^{(2)}$, $\hat{\theta}$ are MLE of θ estimated from data.

Following Csorgo and Horváth (1998), the distribution of $Z_n^{1/2}$ can be approximated as follows:

$$p(Z_n^{1/2} \geq x) \simeq \frac{x^p \exp(-x^2/2)}{2^{p/2}\Gamma(p/2)} \left[\log \frac{(1-h)(1-l)}{h \cdot l} - \frac{p}{x^2} \log \frac{(1-h)(1-l)}{h \cdot l} + \frac{4}{x^2} + O\left(\frac{1}{x^4}\right) \right] \tag{9}$$

as $x \to \infty$, where h and l are $h(n) = l(n) = \frac{(\log n)^{3/2}}{n}$, $p = k_1 + k_2 - k$ is the number of parameters that may change under the alternative, and $\Gamma(\cdot)$ is the gamma function. Thus, the p-value of $Z_n^{1/2}$ and the critical value for rejecting the null hypothesis can both be obtained. Finally, the estimator of t_0 is expressed as follows:

$$\hat{t}_0 = \arg \max_{1 \leq k \leq n} (-2 \log \Lambda_k). \tag{10}$$

3 Data and empirical analysis

Daily closing prices are downloaded from the Datastream for five test markets: Australia (AS51 index), Germany (DAX index), Japan (Nikkei 225 index), Hong Kong (HIS index), and the UK (FTSE 100 index). Daily returns of the S&P 500 index and the monthly growth rate of seven US macroeconomic factors, including the money supply (M2), consumer confidence index (CCI), industrial production (IP), employed population (EP), retail sales (RS), consumer price index (COI), and purchasing manager index (PMI), are included as explanatory variables in the TIR-MIDAS model. We lag the US equity returns by one day as the US market opens later than test markets. The sample period is from 4 January, 2000, to 31 December, 2018.

Descriptive statistics are reported in Table 1. The average log returns to equity markets is very close to zero. The returns are negatively skewed and fat-tailed, and the Jarque-Bera test overwhelmingly rejects the null hypothesis of normality for all markets. The summary statistics provides a clear motivation for

Panel A. Daily stock returns							
	US	Australia	Japan	Germany	HK	UK	
Mean	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000	
Stdev	0.0122	0.0101	0.0153	0.015	0.0151	0.0118	
Skew	-0.2099	-0.7137	-0.4312	-0.0617	-0.2769	-0.1102	
Kurt	9.0682	11.533	9.3338	7.7648	12.468	9.2103	
JB test	13747	14600	7673	4449	17097	7551	
Panel B. Monthly US macroeconomic variable growth							
	M2	CCI	IP	EP	RS	CPI	PMI
Mean	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Stdev	0.0066	0.0756	0.0122	0.0049	0.0157	0.0032	0.0474
Skew	-0.2894	-0.2470	0.5308	-0.0698	-0.1861	-0.3363	0.5549
Kurt	30.589	4.0942	4.8772	20.522	11.11	4.9498	4.3997
JB test	7234	13.64	44.18	2916	626	40.42	30.31

Table 1. Descriptive statistics of daily index returns and macroeconomic variables

In this table, we report the mean, standard deviation (Stdev), skewness (Skew), kurtosis (Kurt), and the Jarque-Bera (JB) test of normality of daily logarithmic stock index returns for US, Australia, Japan, Germany, Hong Kong and the UK in Panel A. Panel B summarizes monthly growth rate for US macroeconomic factors, including the money supply (M2), consumer confidence index (CCI), industrial production (IP), employed population (EP), retail sales (RS), consumer price index (CPI) and purchasing manager index (PMI). The sample period is from 4 January, 2000, to 31 December, 2018.

adopting the TIR model, as returns of all equity markets clearly show fat tails. The monthly growth rate for US macroeconomic variables is also close to zero and left skewed.

The TIR-MIDAS estimation

The TIR-MIDAS coefficient estimates are summarized in Table 2. It is interesting to observe the following. First, the estimates for ω_n are consistently between 0.02 and 0.03 across macroeconomic factors and across markets, suggesting similar weighting scheme for historical S&P returns. Second, the US macroeconomic variables and lags of S&P returns, captured by β_1 and β_2, respectively, often exhibit significant impact on the tail risk of test markets. Finally, the current S&P returns, captured by β_3, are mostly insignificant. Furthermore, it is interesting to note that the UK is substantially affected by all macroeconomic variables we examine and historical S&P returns, whereas Hong Kong is affected by the fewest number of macroeconomic variables.

Structural breaks

We evaluate the time series of maximum likelihood ratio test statistic $-2\log\Lambda_k$ on a daily basis for all test markets. This is illustrated in Figure 1 for Japan. We identify the lowest value for the entire sample period and compute the test statistic for Z_n to assess if any significant structural break exists. The results are reported in Table 3. We observe that one structural break exists in the tail index for all test markets,

	M2	CCI	IP	EP	RS	CPI	PMI
Panel A. Australia							
ω_n	0.0222	0.0229	0.0202	0.0202	0.0225	0.0202	0.0225
w	1.0580***	55.823	1.3462***	1.1329***	1.0138***	28.590	1.1025***
	(0.0000)	(0.2100)	(0.0000)	(0.0000)	(0.0000)	(0.8850)	(0.0000)
β_0	4.2340***	2.5911***	6.8104***	2.4974***	-4.9132***	1.5443***	4.0384***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0033)	(0.0000)
β_1	204.25***	7.8895	210.98***	-136.57	-131.62***	-85.569	13.784***
	(0.0062)	(0.2171)	(0.0000)	(0.1344)	(0.0000)	(0.8688)	(0.0052)
β_2	-118.47**	30.152***	-477.10***	-111.46***	443.31***	17.386	-201.55***
	(0.0250)	(0.0058)	(0.0000)	(0.0052)	(0.0000)	(0.8182)	(0.0000)
β_3	18.449	20.182*	13.089	13.517	19.782*	13.408	19.688*
	(0.1032)	(0.0766)	(0.2960)	(0.2629)	(0.0822)	(0.2686)	(0.0899)
Panel B. Japan							
ω_n	0.0295	0.0287	0.0285	0.0295	0.0285	0.0295	0.0287
w	12.739***	30.225	10.763***	12.835***	5.6114**	10.076***	9.698***
	(0.0018)	(0.5481)	(0.0006)	(0.0025)	(0.0313)	(0.0091)	(0.0058)
β_0	2.0097***	1.3196***	2.4379***	2.1158***	1.8400***	2.1022***	1.3687***
	(0.0000)	(0.0005)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0019)
β_1	-22.001	-14.568*	109.87*	126.13	48.081**	-29.361	-15.619*
	(0.5681)	(0.0890)	(0.0786)	(0.5079)	(0.0455)	(0.7427)	(0.0702)
β_2	43.071**	9.8766	51.581**	43.039**	49.500*	52.663*	37.052*
	(0.0270)	(0.3904)	(0.0143)	(0.0268)	(0.0671)	(0.0777)	(0.0994)
β_3	-12.128	-8.7275	2.1631	-11.812	4.9610	-12.459	-7.266
	(0.4222)	(0.4974)	(0.8548)	(0.4359)	(0.6744)	(0.4107)	(0.5685)
Panel C. Germany							
ω_n	0.0234	0.0235	0.0247	0.0234	0.0246	0.0245	0.0235
w	1.1050***	1.1006**	1.9298	1.1503***	1.9714	0.4452	1.1989
	(0.0001)	(0.0378)	(0.4299)	(0.0000)	(0.3799)	(1.0000)	(0.0000)
β_0	2.4585***	1.8166***	1.3975**	2.5688***	1.1540**	1.0191***	3.0606***
	(0.0000)	(0.0002)	(0.0100)	(0.0000)	(0.0331)	(0.0087)	(0.0000)
β_1	31.567	6.7756**	-73.645**	-189.55**	-34.922**	-129.11***	7.9900**
	(0.1538)	(0.0262)	(0.0084)	(0.0388)	(0.0753)	(0.0092)	(0.0293)
β_2	-99.443***	-50.029	-24.489	-126.99***	-30.181	-1.2806	-162.17***
	(0.0059)	(0.1553)	(0.4500)	(0.0004)	(0.3496)	(0.9707)	(0.0000)
β_3	13.956	10.092	0.2440	13.499*	-5.1115	3.9913	11.3235
	(0.1210)	(0.3209)	(0.9792)	(0.0992)	(0.5598)	(0.6665)	(0.2261)
Panel D. Hong Kong							
ω_n	0.0250	0.0276	0.0276	0.0250	0.0250	0.0276	0.0276
w	7.5723***	17.815	14.792	7.5229**	13.217***	24.666	13.851**
	(0.0005)	(0.1957)	(0.1073)	(0.0247)	(0.0044)	(0.4302)	(0.0281)
β_0	2.5738***	1.6853***	1.8460***	1.7449***	2.1110***	1.9062***	1.7621***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
β_1	104.46***	-5.9966	22.724	-301.44*	51.153***	133.18	-2.3778
	(0.00412)	(0.2659)	(0.7308)	(0.0790)	(0.0019)	(0.2357)	(0.7201)
β_2	77.581***	24.944	30.409	57.685*	34.627**	20.550	33.115*
	(0.0038)	(0.1773)	(0.1823)	(0.0675)	(0.0131)	(0.3387)	(0.0568)
β_3	19.686	6.5595	6.9465	18.088	17.380	8.6208	6.3644
	(0.1382)	(0.6052)	(0.5548)	(0.1426)	(0.2110)	(0.4765)	(0.6009)
Panel E. UK							
ω_n	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247	0.0247
w	133.57	25.850***	637.85	606.91	16.772***	633.06	1.1345***
	(0.4780)	(0.0000)	(1.0000)	(1.0000)	(0.0000)	(1.0000)	(0.0000)
β_0	8.2102***	7.2996***	0.1091	-1.7795***	2.6408***	0.3670	7.5830***
	(0.0000)	(0.0000)	(0.8387)	(0.0031)	(0.0000)	(0.4913)	(0.0000)
β_1	700.40***	42.496***	-104.59**	954.78***	-540.78***	-161.17**	28.436***
	(0.0000)	(0.0000)	(0.0204)	(0.0073)	(0.0003)	(0.0222)	(0.0000)
β_2	43.720**	198.47***	-39.491***	-89.052***	267.67***	-30.919**	-453.62***
	(0.0162)	(0.0000)	(0.0080)	(0.0000)	(0.0004)	(0.0412)	(0.0000)
β_3	18.577	23.093*	18.994	19.389	18.577	19.081	18.577
	(0.1426)	(0.0744)	(0.1379)	(0.1336)	(0.1425)	(0.1362)	(0.1423)

Table 2. Coefficient estimates for the TIR-MIDAS model

This table reports the threshold ω_n and coefficients of the TIR-MIDAS model β_0, β_1, β_2, β_3 and w for test markets: Australia, Japan, Germany, Hong Kong and the UK. The p-values for the estimates are reported in parentheses. The sample period is from 4 January, 2000, to 31 December, 2018.

which naturally divides the sample into two subperiods at the location of the change point (i.e., $Z_n > 11.07$).

Two observations are worth mentioning. First, the location (i.e., the date) of the structural break, shown in bold in Table 3, is quite consistent across test markets from August 2007 in Hong Kong to September 2008 for the UK. These dates fall in the early stage of the Great Recession and are in agreement with market events unfolded at that time. On 24 July, 2007, the largest mortgage lender in the US, Countrywide, issued severe profit warning in the face of rising defaults on subprime loans, which marked the start of the subprime crisis. It is interesting to note that Hong Kong, a global financial center, responded the fastest to the crisis. Second, we note that macroeconomic variables show little impact on the location of structural break, as the time series plot shows very similar pattern across different macroeconomic variables as illustrated in Figure 1 for Japan. In Figure 2, we show the time series of the maximum likelihood ratio test statistic for one macroeconomic variable, the purchasing manager index (PMI), for all test markets. It is interesting to see that its maximum value falls on the location of structural break or is very close to it for all markets.

The existence of structural breaks does not necessarily imply contagion. We next examine the coefficients estimated from the model prior to and after the structural break to determine if contagion between the US and other markets exist.

Financial contagion

In Table 4, we focus on $\hat{\beta}_{12}$ in the second subperiod as the key variable of interest, as it captures the impact of macroeconomic variables on contagion. We notice that for Australia, Japan, and the UK, this coefficient is either insignificant or positively significant, indicating that the tail index widens after the structural break. However, for Germany and the Hong Kong, the coefficients tend to be significantly negative in the second subsample. This is the case for key macroeconomic variables such as the industrial production (IP) and purchasing manager index (PMI) for Germany, a key production-oriented economy, and the consumer confidence index (CCI) and retail sales (RS) for Hong Kong. These variables are insignificant prior to the break structural, thus the significantly negative coefficients indicate a much narrow tail index, and the increased chance of market downturn should the US market is in distress. Hence, contagion exists between the US as the originating country and Germany and the Hong Kong as the recipient economies.

	M2	CCI	IP	EP	RS	CPI	PMI
Panel A. Australia							
$-K_n(\theta)$	20.448	20.639	22.936	21.164	20.833	23.835	20.449
$-K_n(\theta)$ (Change)	34.155	34.155	34.155	34.155	34.155	35.752	30.770
Z_n	**27.414**	27.033	22.438	25.984	26.645	20.642	27.412
Location	**2008.7.25**	2008.7.25	2008.7.25	2008.7.25	2008.7.25	2008.7.25	2008.7.25
Panel B. Japan							
$-K_n(\theta)$	3.8997	1.0942	1.6550	6.2088	5.1359	3.1117	1.3087
$-K_n(\theta)$ (Change)	26.502	23.336	24.468	28.629	27.563	24.636	23.830
Z_n	45.205	**44.483**	45.626	44.840	44.855	43.048	45.043
Location	2008.7.18	**2008.1.22**	2008.1.22	2008.7.18	2008.1.22	2008.1.22	2008.7.18
Panel C. Germany							
$-K_n(\theta)$	24.880	24.501	20.039	22.765	23.327	22.656	21.086
$-K_n(\theta)$ (Change)	47.126	47.865	47.468	46.312	47.640	47.380	47.468
Z_n	44.492	46.727	**54.859**	47.093	48.627	49.449	52.764
Location	2008.1.22	2007.11.21	**2008.2.1**	2008.2.1	2007.11.21	2008.2.1	2008.2.1
Panel D. Hong Kong							
$-K_n(\theta)$	18.268	14.418	13.215	16.286	17.773	15.512	13.180
$-K_n(\theta)$ (Change)	37.598	38.038	38.038	38.038	38.038	37.562	37.754
Z_n	38.661	47.240	**49.647**	43.503	40.529	44.101	49.147
Location	2007.7.27	2007.8.24	**2007.8.24**	2007.8.24	2007.8.24	2007.7.27	2007.8.24
Panel E. UK							
$-K_n(\theta)$	39.710	33.433	39.599	39.371	38.626	39.557	39.710
$-K_n(\theta)$ (Change)	49.430	49.430	49.430	49.430	49.430	49.430	49.430
Z_n	19.440	**31.995**	19.662	20.118	21.608	19.746	19.440
Location	2008.9.8	**2008.9.8**	2008.9.8	2008.9.8	2008.9.8	2008.9.8	2008.9.8

Table 3. Likelihood ratio test for structural breaks

This table reports the likelihood ratio test statistics for identifying the existence and location of structural breaks for test markets. The location of structural break refers to the day when the null hypothesis of no structural break is most significantly rejected by the likelihood ratio test and highlighted in bold font. The sample period is from 4 January, 2000, to 31 December, 2018.

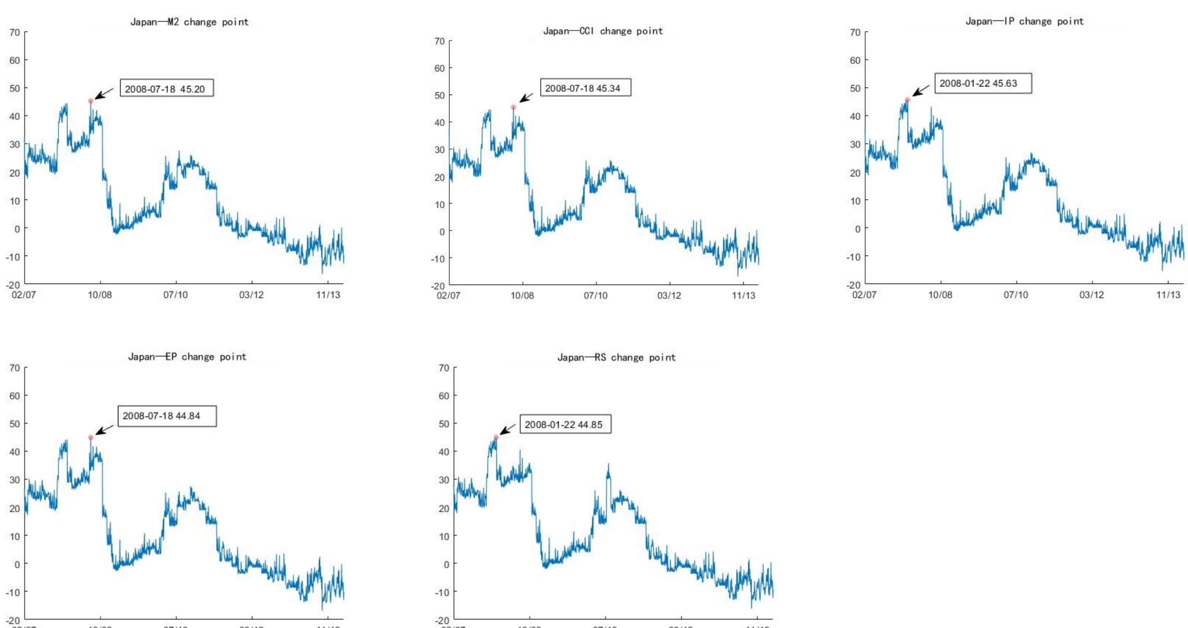

Figure 1. The figure plots the time series of maximum likelihood ratio test statistic $-2\log\Lambda_k$ for all macroeconomic variables for Japan. The sample period is from 4 January, 2000, to 31 December, 2018.

	M2	CCI	IP	EP	RS	CPI	PMI
Panel A. Australia							
$\hat{w}_1$	9.0463	5.0909	8.5025	9.2306	9.4119	9.5626	4.9613
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
$\hat{\beta}_{01}$	1.2215	1.8512	1.3108	1.2692	1.2573	1.2664	1.2019
	(0.4564)	(0.6331)	(0.4189)	(0.9251)	(0.4277)	(0.4576)	(0.3872)
$\hat{\beta}_{11}$	-6.1247	7.5982	-7.8988	5.2623	-3.9950	-2.4351	-2.5900
	(0.99999)	(0.9991)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
$\hat{\beta}_{21}$	-12.083	-2.9344	-10.833	-12.533	-12.928	-13.281	-0.2072
	(0.9996)	(0.9999)	(0.9999)	(1.0000)	(0.9999)	(1.0000)	(1.0000)
$\hat{\beta}_{31}$	7.1131	7.1131	7.1131	7.1131	7.1131	7.1131	7.1131
	(0.7991)	(0.7991)	(0.7991)	(0.7991)	(0.7991)	(0.7991)	(0.7991)
$\hat{w}_2$	6.3064	2.7204	16.5092	3.0664	8.6166	2.8411	2.7691
	(0.8534)	(0.7240)	(0.9108)	(0.9469)	(0.9996)	(0.7158)	(0.8344)
$\hat{\beta}_{02}$	2.6621***	1.4934**	1.5170**	1.7917**	1.4821**	1.4932**	1.2704*
	(0.0002)	(0.0335)	(0.0305)	(0.0106)	(0.0350)	(0.0335)	(0.0701)
$\hat{\beta}_{12}$	245.44**	5.1725	111.16	191.52	26.998	188.77	2.9745
	(0.0146)	(0.3641)	(0.4361)	(0.2049)	(0.9001)	(0.5676)	(0.8568)
$\hat{\beta}_{22}$	-26.005	-22.449	5.3167	-3.9467	0.8097	-21.560	-11.901
	(0.8758)	(0.7326)	(0.8611)	(0.9543)	(0.9996)	(0.79134)	(0.8461)
$\hat{\beta}_{32}$	5.4374	5.3038	4.7821	4.3614	4.0504	4.0932	4.5741
	(0.6076)	(0.6450)	(0.6531)	(0.6863)	(0.7173)	(0.7151)	(0.6896)
Panel B. Japan							
$\hat{w}_1$	23.783	2.7804	2.1279***	18.148	2.1035***	1.8634	1.9190
	(0.5854)	(0.0821)	(0.0000)	(0.6613)	(0.0000)	(0.4979)	(0.8094)
$\hat{\beta}_{01}$	1.4070**	1.8279	-6.0211***	1.0474**	14.670***	-0.5911	1.2662*
	(0.0118)	(0.1218)	(0.0023)	(0.0389)	(0.0000)	(0.6594)	(0.0766)
$\hat{\beta}_{11}$	72.383	-7.7518	-1167.0***	-228.63	605.13***	-289.49	7.9811
	(0.3769)	(0.5524)	(0.0000)	(0.4484)	(0.0000)	(0.3493)	(0.4513)
$\hat{\beta}_{21}$	-6.7885	-126.33	711.65***	-5.7825	-961.77***	161.45**	10.975
	(0.7055)	(0.1513)	(0.0000)	(0.7383)	(0.0000)	(0.0385)	(0.8574)
$\hat{\beta}_{31}$	-9.0959	0.1197	0.1196	-9.0959	0.1193	0.1196	-8.9268
	(0.4872)	(0.9947)	(0.9948)	(0.4948)	(0.9947)	(0.9949)	(0.5046)
$\hat{w}_2$	0.9695***	14.328	11.871	1.0106**	3.3810	2.2747	578.00
	(0.0000)	(0.5961)	(0.6473)	(0.0306)	(0.3459)	(0.3342)	(1.0000)
$\hat{\beta}_{02}$	0.5334	1.2716***	1.3000***	0.8783***	0.4898	0.8200	1.9222***
	(0.1835)	(0.0018)	(0.0036)	(0.0003)	(0.4141)	(0.1564)	(0.0015)
$\hat{\beta}_{12}$	-92.805	-1.4766	37.182	-102.77	-53.221	110.78	83.509*
	(0.1376)	(0.5561)	(0.3537)	(0.1468)	(0.1136)	(0.3077)	(0.0900)
$\hat{\beta}_{22}$	9.5666	-17.893	-16.120	3.8895	-41.570	-54.568	17.792
	(0.4789)	(0.3331)	(0.3677)	(0.8478)	(0.3405)	(0.5467)	(0.1076)
$\hat{\beta}_{32}$	-10.115	-5.0520	-5.2110	-10.841	-0.5269	-5.0411	-6.2187
	(0.4406)	(0.4269)	(0.4162)	(0.4111)	(0.9344)	(0.4324)	(0.6565)
Panel C. Germany							
$\hat{w}_1$	14.051	24.662	15.622	14.146	38.899	16.011	18.610
	(0.9692)	(0.9872)	(0.8244)	(0.6655)	(0.6292)	(0.9559)	(0.8067)
$\hat{\beta}_{01}$	1.0286	0.8596	1.0680	1.0382	0.9089	1.0210	0.9781
	(0.2068)	(0.3642)	(0.1861)	(0.1991)	(0.3182)	(0.2074)	(0.2259)
$\hat{\beta}_{11}$	-1.2867	-2.1820	-10.236	2.6789	6.7240	-5.3340	0.6129
	(0.9989)	(0.9901)	(0.9652)	(0.9919)	(0.9628)	(0.9964)	(0.9636)
$\hat{\beta}_{21}$	-28.856	-29.003	-25.196	-28.665	-24.418	-26.624	-26.113
	(0.9238)	(0.9761)	(0.8050)	(0.4450)	(0.2128)	(0.9401)	(0.5313)
$\hat{\beta}_{31}$	18.659	34.384	18.659	18.659	34.384	18.659	18.659
	(0.2454)	(0.1201)	(0.2453)	(0.2453)	(0.1201)	(0.2454)	(0.2453)
$\hat{w}_2$	10.085	15.203	1.0860***	7.2039	2.9667**	1.0664***	37.665*
	(0.7720)	(0.7041)	(0.0000)	(0.3447)	(0.0294)	(0.0000)	(0.0553)
$\hat{\beta}_{02}$	1.3912**	1.4104***	1.1369***	1.4963***	0.3469	1.7783***	2.5503***
	(0.0102)	(0.0030)	(0.0000)	(0.0045)	(0.5180)	(0.0000)	(0.0000)
$\hat{\beta}_{12}$	14.297	-3.3422	-62.812*	195.15	124.04*	230.14*	-55.869***
	(0.5775)	(0.1341)	(0.0853)	(0.1245)	(0.0668)	(0.0835)	(0.0004)
$\hat{\beta}_{22}$	11.712	8.4690	261.17	31.831	-100.96**	213.55	-26.527**
	(0.6743)	(0.6325)	(0.1513)	(0.2971)	(0.0110)	(0.2667)	(0.0278)
$\hat{\beta}_{32}$	10.650	-5.7660	0.4790	-3.6143	-8.2755	3.4644	7.0193
	(0.1695)	(0.5834)	(0.9262)	(0.7267)	(0.5289)	(0.6241)	(0.3691)
Panel D. Hong Kong							
$\hat{w}_1$	8.6575	4.9296	15.381	15.870	11.111	8.7258	4.5739
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
$\hat{\beta}_{01}$	1.5430	1.3247	1.8104*	1.8317*	1.7096*	1.5778	1.2159
	(0.6076)	(0.3618)	(0.07304)	(0.06641)	(0.09494)	(0.84537)	(0.41544)
$\hat{\beta}_{11}$	-3.9355	-3.4519	5.3219	2.5928	12.886	3.7727	-6.0231
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
$\hat{\beta}_{21}$	10.375	0.4599	18.344	18.828	14.045	10.484	1.2261
	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)	(1.0000)
$\hat{\beta}_{31}$	-35.070	-33.185	-33.185	-33.185	-33.185	-35.0705	-33.185
	(0.4569)	(0.7421)	(0.6863)	(0.7397)	(0.7441)	(0.4616)	(0.6059)
$\hat{w}_2$	908.59	1.0659***	1006.5	1.5596***	2.4419***	10.145	1.0299***
	(1.0000)	(0.0000)	(1.0000)	(0.0006)	(0.0000)	(0.1734)	(0.0000)
$\hat{\beta}_{02}$	1.3867**	8.4448***	1.2364**	1.2108	-2.3026	1.6882***	1.7890***
	(0.0350)	(0.0002)	(0.0186)	(0.1172)	(0.2509)	(0.0065)	(0.0029)
$\hat{\beta}_{12}$	-83.629	-63.405***	61.892	528.16*	-1793.4*	-497.02	-41.636
	(0.5425)	(0.0001)	(0.2462)	(0.0744)	(0.0532)	(0.1440)	(0.1075)
$\hat{\beta}_{22}$	15.853*	-1741.6***	-4.2778	-120.34	879.36*	95.114	-206.45
	(0.0879)	(0.0001)	(0.7699)	(0.1910)	(0.0665)	(0.1956)	(0.1281)
$\hat{\beta}_{32}$	14.582	-7.4101	-10.073	-7.4100	-7.4100	13.195	-12.734
	(0.4569)	(0.7421)	(0.6863)	(0.7397)	(0.7441)	(0.4616)	(0.6059)

	M2	CCI	IP	EP	RS	CPI	PMI
Panel E. UK							
$\hat{w}_1$	2.3477	23.041***	1.3040	1.5295**	1.5663*	1.6389***	18.527
	(0.2456)	(0.0000)	(0.3513)	(0.0395)	(0.0701)	(0.0000)	(0.5575)
$\hat{\beta}_{01}$	0.3743	8.3973***	0.1494	-1.0279	-3.9977***	-5.9718***	1.8765**
	(0.6473)	(0.0000)	(0.8510)	(0.2022)	(0.0000)	(0.0000)	(0.0183)
$\hat{\beta}_{11}$	55.239	40.981***	73.684	-77.577	-60.731	-360.57**	4.7936
	(0.5206)	(0.0000)	(0.2821)	(0.5246)	(0.5652)	(0.0233)	(0.4374)
$\hat{\beta}_{21}$	110.46*	285.59***	70.330	173.68***	383.32***	593.23***	34.729
	(0.0551)	(0.0000)	(0.2303)	(0.0012)	(0.0000)	(0.0000)	(0.2973)
$\hat{\beta}_{31}$	17.898	17.898	17.898	17.898	17.898	17.898	17.898
	(0.2198)	(0.2196)	(0.2197)	(0.2197)	(0.2074)	(0.2079)	(0.2196)
$\hat{w}_2$	2.2738	32.564	0.5583	2.0430	34.529	276.76	2.3137
	(0.9644)	(0.9958)	(1.0000)	(0.7201)	(0.9219)	(0.9993)	(0.3666)
$\hat{\beta}_{02}$	2.2877**	3.8070***	2.4860**	1.3869	2.1772**	2.2970**	-0.2975
	(0.0129)	(0.0000)	(0.0189)	(0.1419)	(0.0179)	(0.0126)	(0.8578)
$\hat{\beta}_{12}$	136.68	29.986	281.30	149.41	198.34	635.81	-51.454
	(0.1671)	(0.9458)	(0.2392)	(0.1425)	(0.5172)	(0.3189)	(0.1100)
$\hat{\beta}_{22}$	-5.8318	39.719	-3.9682	-68.224	-39.431	-11.599	-236.99*
	(0.9717)	(0.9920)	(0.9648)	(0.6889)	(0.7515)	(0.7117)	(0.0770)
$\hat{\beta}_{32}$	-17.291	-17.291	-17.291	-17.291	-17.291	-17.291	-17.291
	(0.3652)	(0.3652)	(0.3667)	(0.3652)	(0.3652)	(0.36523)	(0.3651)

Table 4. Coefficient estimates for the TIR-MIDAS model for subsamples

This table reports coefficients estimates for subsamples. The coefficients $\widehat{\beta_{01}}$, $\hat{\beta}_{11}$, $\hat{\beta}_{21}$, $\hat{\beta}_{31}$, and $\hat{w}_1$ are estimated for the first period prior to the structural break, whereas $\hat{\beta}_{02}$, $\hat{\beta}_{12}$, $\hat{\beta}_{22}$, $\hat{\beta}_{32}$, and $\hat{w}_2$ are estimated for the second period, respectively. The p-values for the estimates are reported in parentheses.

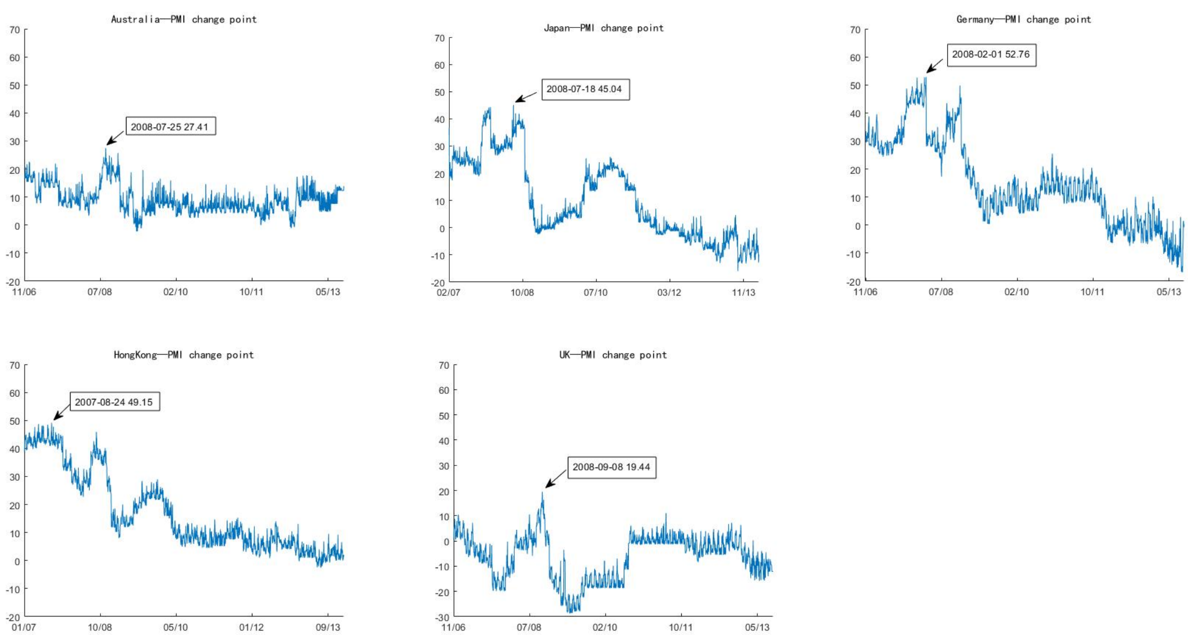

Figure 2. The figure plots the time series of maximum likelihood ratio test statistic $-2\log\Lambda_k$ for the purchasing manager index for all test markets. The sample period is from 4 January, 2000, to 31 December, 2018.

4 Conclusion

In this paper, we offer a theoretically well-grounded method for assessing contagion in international equity markets. It involves dividing the sample at statistically significant structural breaks, which are determined by the MLE of the tail index regression model, and estimating and comparing regression coefficients in the subsamples. We use losses to the S&P 500 index and information in US macroeconomic variables, combined via the mixed data sampling technique, as explanatory variable and explore their impact on market returns in Australia, Japan, Germany, Hong Kong, and the UK. Our empirical results suggest that all test markets under investigation have gone through a structural break in their relation to the US market but only Germany and Hong Kong are vulnerable to market downturn in the US.

References

Asgharian, H., Hou, A. J., Javed, F., 2013. The importantce of the macroeconomic variables in forecasting stock return variance: A GARCH-MIDAS approach. Journal of Forecasting 32, 600–612.

Beirlant, J., Figueiredo, F., Gomes, M. I., Vandewalle, B., 2008. Improved reduced-bias tail index and quantile estimators. Journal of Statistical Planning and Inference 138, 1851–1870.

Bekaert, G., Harvey, C. R., Ng, A., 2005. Market integration and contagion. Journal of Business 78, 39–69.

Csorgo, M., Horváth, L., 1998. Limit Theorems in Change-Point Analysis. Wiley, Chichester.

Engle, R. F., Ghysels, E., Sohn, B., 2013. Stock market volatility and macroeconomic fundamentals. Review of Economics and Statistics 95, 776–797.

Fang, L., Chen, B., Yu, H., Xiong, C., 2018. The effect of economic policy uncertainty on the long-run correlation between crude oil and the U.S. stock markets. Finance Research Letters 24, 56–63.

Favero, C. A., Giavazzi, F., 2002. Is the international propagation of financial shocks non-linear? Evidence from the EMR. Journal of International Economics 57, 231–246.

Ghysels, E., Santa-Clara, P., Walkanov, R., 2004. The MIDAS touch: Mixed data sampling regression models, UCLA Working Paper.

Ghysels, E., Sinko, A., Valkanov, R., 2007. MIDAS regressions: Further results and new directions. Econometric Reviews 26, 53–90.

Gomes, M. I., De Haan, L., Rodrigues, L. H., 2008. Tail index estimation for heavy-tailed models: Accommodation of bias in weighted log-excesses. Journal of the Royal Statistical Society: Series B 70, 31–52.

Hill, B., 1975. A simple general approach to inference about the tail of a distribution. Annals of Mathematics Statistics 3, 1163–1174.

Huisman, R., Koedijk, K. G., Kool, C. J. M., Palm, F., 2001. Tail-index estimates in small samples. Journal of Business & Economic Statistics 19, 208–216.

Jin, X., 2016. The impact of 2008 financial crisis on the efficiency and contagion of Asian stock markets: A Hurst exponent approach. Finance Research Letters 17, 167–175.

Lei, L., Shang, Y., Chen, Y., Wei, Y., 2019. Does the financial crisis change the economic risk perception of crude oil traders? a MIDAS quantile regression approach. Finance Research Letters 30, 341–351.

Mensi, W., Hammoudeh, S., Yoon, S.-M., Nguyen, D. K., 2016. Asymmetric linkages between BRICS stock returns and country risk ratings: Evidence from dynamic panel threshold models. Review of International Economics 24, 1–19.

Pericoli, M., Sbracia, M., 2003. A primer on financial contagion. Journal of Economic Surveys 17, 571–608.

Rodriguez, J. C., 2007. Measuring financial contagion: A copula approach. Journal of Empirical Finance 14, 401–423.

Wang, H., Tsai, C.-L., 2009. Tail index regression. Journal of the American Statistical Association 104, 1233–1240.

Wei, Y., Qin, S., Li, X., Zhu, S., Wei, G., 2019. Oil price flucuation, stock market and macroeconomic fundamentals: Evidence from China before and after the financial crisis. Finance Research Letters 30, 23–29.

Yang, J., Bessler, D. A., 2008. Contagion around the October 1987 stock market crash. European Journal of Operational Research 184, 291–310.

Ye, W., Liu, X., Miao, B., 2012. Measuring the subprime crisis contagion: Evidence of change point analysis of copula functions. European Journal of Operational Research 222, 96–103.

Ye, W., Luo, K., Liu, X., 2017. Time-varying quantile association regression model with applications to financial contagion and VaR. European Journal of Operational Research 256, 1015–1028.